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ART UNIT	**PAPER NUMBER**
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Please find below and/or attached an Office communication concerning this application or proceeding.

Office Action Summary	Application No.	Applicant(s)	
	09/833,377	CAHILL, NATHAN D.	
	Examiner	**Art Unit**	MN
	Kevin Siangchin	2623	

-- The MAILING DATE of this communication appears on the cover sheet with the correspondence address --

Period for Reply

A SHORTENED STATUTORY PERIOD FOR REPLY IS SET TO EXPIRE 3 MONTH(S) FROM THE MAILING DATE OF THIS COMMUNICATION.

- Extensions of time may be available under the provisions of 37 CFR 1.136(a). In no event, however, may a reply be timely filed after SIX (6) MONTHS from the mailing date of this communication.
- If the period for reply specified above is less than thirty (30) days, a reply within the statutory minimum of thirty (30) days will be considered timely.
- If NO period for reply is specified above, the maximum statutory period will apply and will expire SIX (6) MONTHS from the mailing date of this communication.
- Failure to reply within the set or extended period for reply will, by statute, cause the application to become ABANDONED (35 U.S.C. § 133). Any reply received by the Office later than three months after the mailing date of this communication, even if timely filed, may reduce any earned patent term adjustment. See 37 CFR 1.704(b).

Status

1)☐ Responsive to communication(s) filed on _____.

2a)☐ This action is **FINAL**. 2b)☒ This action is non-final.

3)☐ Since this application is in condition for allowance except for formal matters, prosecution as to the merits is closed in accordance with the practice under *Ex parte Quayle*, 1935 C.D. 11, 453 O.G. 213.

Disposition of Claims

4)☒ Claim(s) *1-44* is/are pending in the application.

4a) Of the above claim(s) _____ is/are withdrawn from consideration.

5)☐ Claim(s) _____ is/are allowed.

6)☒ Claim(s) *1-44* is/are rejected.

7)☐ Claim(s) _____ is/are objected to.

8)☐ Claim(s) _____ are subject to restriction and/or election requirement.

Application Papers

9)☒ The specification is objected to by the Examiner.

10)☒ The drawing(s) filed on *12 April 2001* is/are: a)☒ accepted or b)☐ objected to by the Examiner.

Applicant may not request that any objection to the drawing(s) be held in abeyance. See 37 CFR 1.85(a).

Replacement drawing sheet(s) including the correction is required if the drawing(s) is objected to. See 37 CFR 1.121(d).

11)☐ The oath or declaration is objected to by the Examiner. Note the attached Office Action or form PTO-152.

Priority under 35 U.S.C. § 119

12)☐ Acknowledgment is made of a claim for foreign priority under 35 U.S.C. § 119(a)-(d) or (f).

a)☐ All b)☐ Some * c)☐ None of:

1.☐ Certified copies of the priority documents have been received.

2.☐ Certified copies of the priority documents have been received in Application No. _____.

3.☐ Copies of the certified copies of the priority documents have been received in this National Stage application from the International Bureau (PCT Rule 17.2(a)).

* See the attached detailed Office action for a list of the certified copies not received.

Attachment(s)

1) ☒ Notice of References Cited (PTO-892)

2) ☐ Notice of Draftsperson's Patent Drawing Review (PTO-948)

3) ☒ Information Disclosure Statement(s) (PTO-1449 or PTO/SB/08) Paper No(s)/Mail Date *2 / 20 April 2000*.

4) ☐ Interview Summary (PTO-413) Paper No(s)/Mail Date. _____ .

5) ☐ Notice of Informal Patent Application (PTO-152)

6) ☐ Other: _____.

Detailed Action

Specification

Objections

1. The disclosure is objected to because of the following informalities. In the Summary of Invention, the applicant refers repeatedly to "determining a fitting error between the objective function and the data" (e.g. page 4, lines 15-16 of the applicant's disclosure). Typically, in optimization problems (such as those dealt with in applicant's claimed invention), an *objective function* is the function to be optimized. Generally, when optimizing mathematical models, the objective function is a measure of the *goodness-of-fit* of the model to the data being modeled. Given such a definition, the phrase "determining a fitting error between the objective function and the data" would mean, "determining a fitting error between the fitting error and the data", which clearly makes no sense. Furthermore, the applicant's usage of objective function in that phrase is inconsistent with its correct usage in the subsequent portions (e.g. the value after Minimize in equation (3) on page 12 of the applicant's disclosure) of the specification. Appropriate correction is required.

Claims

Objections

2. Claims 1 and 14 are objected to because of the following informalities. Claims 1 and 14 state, "comparing said fitting error to stopping criteria to determine if said fitting error is satisfied". It is apparent from the specification and subsequent claims that the applicant intended this phrase to be "comparing said fitting error to stopping criteria to determine if said *stopping criteria* is satisfied". Claims 1 and 14 will be interpreted in this manner henceforth in this document. Appropriate correction is required.

Rejections Under U.S.C. § 101

3. 35 U.S.C. 101 reads as follows:

> Whoever invents or discovers any new and useful process, machine, manufacture, or composition of matter, or any new and useful improvement thereof, may obtain a patent therefor, subject to the conditions and requirements of this title.

4. Claims 1-26 are rejected under 35 U.S.C. 101 because the claimed invention is directed to non-statutory subject matter. With regard to claims 1-13, the method of fitting proposed therein constitutes non-statutory subject matter because the process of fitting a plurality of functions to input data represents a purely mathematical calculation or algorithm, which, in and of itself, is devoid of a concrete and tangible result directed to a specific practical application. Claims 14-26 are similarly rejected.

Rejections Under U.S.C. § 112(1)

5. The following is a quotation of the first paragraph of 35 U.S.C. 112:

> The specification shall contain a written description of the invention, and of the manner and process of making and using it, in such full, clear, concise, and exact terms as to enable any person skilled in the art to which it pertains, or with which it is most nearly connected, to make and use the same and shall set forth the best mode contemplated by the inventor of carrying out his invention.

6. Claims 6, 19, 29, and 38 are rejected under 35 U.S.C. 112, first paragraph, as failing to comply with the enablement requirement. The claim(s) contains subject matter which was not described in the specification in such a way as to enable one skilled in the art to which it pertains, or with which it is most nearly connected, to make and/or use the invention.

7. Nowhere in the specification does the applicant indicate that the objective function be defined as a vector representation of a plurality of function parameters. Instead the applicant does mention a vector referred to as a *chromosome* that represents a plurality of function parameters attributed to a collection of probability distributions (see page 23, lines 9-19 of the applicant's specification). This vector, however, is not associated with the objective function.

Rejections Under U.S.C. § 112(2)

8. The following is a quotation of the second paragraph of 35 U.S.C. 112:

> The specification shall conclude with one or more claims particularly pointing out and distinctly claiming the subject matter which the applicant regards as his invention.

9. Claims 1, 6, 13, 14, 19, 26, 27, 29, 35, 36, 38, and 44 are rejected under 35 U.S.C. 112, second paragraph, as being indefinite for failing to particularly point out and distinctly claim the subject matter which applicant regards as the invention.

10. *The following is in regard to Claims 1, 13, 14, 26, 27, 35, 36, and 44.* These claims refer to a "fit error" or "fitting error between said objective function and the data". Following from the discussion given above in paragraph 1 of this document regarding objective functions, these portions of the said claims do not make sense. Furthermore, "determining a fitting error between said objective function and the data" (e.g. claim 1) or "minimiz[ing] the magnitude of the fit error between said objective function and the data" (e.g. claim 13) is not consistent with the usage of the objective function set forth in the applicant's specification (not including the flawed Summary of Invention).

11. For the remainder of this document, claim 1 will be interpreted as:

A method of fitting a plurality of sub-population functions to data, comprising the steps of:

a. defining a plurality of functions according to a plurality of function parameters and a total number of functions;

b. generating a <u>modeling function</u> based on said plurality of function parameters;

c. determining an <u>objective function</u> that measures the fitting error between said modeling function and the data,

d. and comparing said fitting error to stopping criteria to determine if said stopping criteria is satisfied.

Note that the modeling function referred to above corresponds to the function defined in equation (1) of the applicant's specification and reference number 8 of applicant's Fig. 1. Claims 14, 27, and 36 will be interpreted similarly.

12. For the remainder of this document, claim 13 will be interpreted as: The method of claim 12, wherein said fitness function is optimized to minimize the magnitude of the fit error between said *modeling function* and the data. Claims 26, 35, and 44 will be interpreted similarly.

13. *The following is in regard to Claims 6, 19, 29, and 38.* These claims recite, "said objective function is defined as a vector representation of said plurality of function parameters". While the objective function is certainly dependant on the plurality of function parameters, it should not be considered a representation of those parameters, particularly when taking into account its usage in the applicant's claimed invention and, more generally, the usage of objective functions in the optimization problems encountered in the prior art. Expressing the modeling function (see above) as a vector representation of said plurality of function parameters would be more consistent with the applicant's specification (e.g. page 23, lines 9-19 of the applicant's specification). This interpretation, as applied to claims 6, 19, 29, and 38, is adopted for the remainder of this document. For example, claim 6 will be interpreted as, "The method of Claim 1, wherein said *modeling function* is defined as a vector representation of said plurality of function parameters".

Rejections Under U.S.C. § 102(b)

14. The following is a quotation of the appropriate paragraphs of 35 U.S.C. 102 that form the basis for the rejections under this section made in this Office action:

> A person shall be entitled to a patent unless –
>
> (b) the invention was patented or described in a printed publication in this or a foreign country or in public use or on sale in this country, more than one year prior to the date of application for patent in the United States.

15. Claims 1, 12-14, and 25-26 are rejected under 35 U.S.C. 102(b) as being anticipated by Press et al. ("Numerical Recipes in C" © 1992, Cambridge University Press).

16. *The following is in regard to Claim 1.* Before proceeding, it should be noted that the language of claim 1 is so broad as to encompass nearly all techniques to fit data to a mathematical model. Press et al. discuss, generally, techniques used to model data. The discussion is directed, in particular, to the technique of *least squares fitting* (e.g. Press et al., Section 15.4, *General Linear Least Square Fitting*). According to Press et al. (page 656, first and second paragraphs), the modeling of data generally involves the fitting of a data to a model, consisting of a convenient class of functions that depend on adjustable parameters. Since such functions are representative of sub-populations of the data, the class of functions can be regarded as a *plurality of sub-population functions*.

17. In the case of linear least squares, Press et al. refer to these functions as *basis functions* (i.e. $\{X_k(x)\}_{k=1...M}$ – Press et al. page 671, second paragraph). The data being fit are data points (x_i, y_i). See first paragraph on page 671 of Press et al. The linear least squares method includes the following steps:

a. Defining a plurality of functions according to a plurality of function parameters and a total number of functions. See, for example, Press et al. equation (15.4.2) on page 671 and the explanatory discussion therein. According to Press et al. equation (15.4.2), a plurality of functions (i.e. $\{a_k X_k(x)\}_{k=1...M}$) is defined according to a plurality of function parameters (i.e. $\{a_k\}_{k=1...M}$) and a total number of functions (i.e. M). See also the discussion in paragraph two on page 656 of Press et al.

b. Generating a modeling function based on a said plurality of function parameters. Again, refer to equation (15.4.2) of Press et al. There, the modeling function is $y(x)$.

c. Determining an objective function measuring the fitting error between said modeling function and the data. Refer to equation (15.4.3) and note that this value (referred to hereinafter as chi-squared) is what Press et al. refer to as a *figure-of-merit function* (Press et al. page 656 paragraph 2). In other words, chi-squared gives an indication as to the fitting error between the modeling function and the data. This is evident from the numerator of the summand in Press et al. equation (15.4.3). Chi-squared, therefore, is an objective function measuring the fitting error between said modeling function and the data.

d. Comparing said fitting error to stopping criteria to determine if said fitting error is satisfied. The linear least squares method described by Press et al. attempts to minimize Press et al. equation

(15.4.3). This minimization is achieved when the criterion set forth in Press et al. equation (15.4.6) (page 672 of Press et al.) is satisfied. In this manner, Press et al. equation (15.4.6) represents a stopping criterion against which the fitting error (chi-squared) is compared.

It has thus been shown that the method of linear least squares, as described by Press et al., is indeed a method of fitting that conforms to claim 1. Therefore, the method put forth in applicant's claim 1 is anticipated by the method of linear least squares.

18. *The following is in regard to Claim 6.* As shown above, Press et al. teach a method in accordance with claim 1. Typically, functions that are discretized in order to be manipulated by a digital computing device, such as a computer, are represented as discrete vectors of finite dimension. This is apparent from the C code listed on pages 674-675 of Press et al. The vector **afunc** represents the basis functions described above. Given such a representation, the modeling function defined in Press et al. equation (15.4.2) then becomes a sum of weighted vectors **afunc**. Consequently, the objective function defined in Press et al. equation (15.4.2) becomes a vector. Therefore, the teachings of Press et al. implicitly entail the representation of the objective function as a vector. In this way, the teachings of Press et al. anticipate the method put forth by the applicant in claim 6.

19. *The following is in regard to Claim 12.* As shown above, Press et al. teach a method in accordance with claim 1. Also mentioned above, relative to claim 1, the stopping criterion, defined by Press et al. equation (15.4.6), is based on a figure-of-merit function, chi-squared. Chi-squared can be considered a fitness function, in a similar vein as the applicant, since it is a function providing a measure of the goodness-of-fit of the model to the input data. In this way, the method put forth by the applicant in claim 12 is anticipated by the method of linear least squares.

20. *The following is in regard to Claim 13.* As just shown, Press et al. teach a method in accordance with claim 12. As mentioned above, with regard to claim 1, the aim of the linear least squares method is to minimize chi-squared with respect to the parameter set $\{a_k\}_{k=1...M}$. Again, chi-squared provides a measure of the magnitude of fitting error between the modeling function and the data. Therefore, the method put forth by the applicant in claim 13 is anticipated by the method of linear least squares.

21. *The following is in regard to Claims 14 and 25-26.* These claims recite substantially the same limitations as claims 1 and 12-13, respectively. Therefore, with regard to claims 14 and 25-26, remarks analogous to those presented above with regard to claims 1 and 12-13 are, respectively, applicable.

22. Claim 1, 3-6, 9, 11-13, 14, 16-19, 22, and 24-26 are rejected under 35 U.S.C. 102(b) as being anticipated by Snyder et al. ("Optimal Thresholding – A New Approach", Pattern Recognition Letters, 1990).

23. *The following is in regard to Claim 1.* Snyder et al. describe the fitting of a plurality of sub-population functions (a mixture of gaussian probability density functions (pdfs)) to data. See *Section I. Introduction*, paragraphs 1-2 on page 803 of Snyder et al. This fitting technique comprises steps of:

a. Defining a plurality of functions (these functions will be referred to, interchangeably, with *basis functions* henceforth in this document) according to a plurality of function parameters and a total number of functions. See *Section I. Introduction*, paragraphs 2 on page 803 of Snyder et al. Note, in particular, equation (1). Equation (1) consists of a plurality of gaussians (i.e. $\left\{\frac{1}{\sqrt{2\pi\sigma_i}}\exp\left[-\frac{(x-\mu_i)^2}{\sigma_i^2}\right]\right\}_{i=1\ldots d}$) which are dependant on the sets parameters $\{\mu_i, \sigma_i\}_{i=1\ldots d}$. Also defined is a total number of functions d.

b. Generating a modeling function based on said plurality of function parameters. See *Section I. Introduction*, paragraphs 2 on page 803 of Snyder et al. Note, in particular, equation (1). The modeling function is *h(x)*.

c. Determining an objective function measuring the fitting error between said modeling function and the data. See the last paragraph on page 803 of Snyder et al. The value H defined in equation (4) of Snyder et al. can be considered an objective function measuring the fitting error between said modeling function (*h(x)*)and the data (h_j).

d. Comparing said fitting error to stopping criteria to determine if said stopping criteria is satisfied. This is implied by the minimization of the objection function (H) discussed in the last paragraph on page 803 of Snyder et al. to the first paragraph on page 804 of Snyder et al. It would be understood by one of ordinary skill in the art that such a minimization would involve a

comparison of *H*, which is indicative of the fitting error, to a stopping criteria (i.e. a value considered minimal).

It has thus been shown that the fitting technique, as described by Snyder et al., is indeed a method of fitting that conforms to claim 1. Therefore, the method put forth in applicant's claim 1 is anticipated by the teachings of Snyder et al.

24. *The following is in regard to Claim 3.* As shown above, Snyder et al. show a method of fitting in accordance with claim 1. Snyder et al. further disclose determining an optimum threshold that delineates said plurality of functions. See the second paragraph of Section I. *Introduction* on page 803 of Snyder et al. Note in particular equation (2). Therefore, the method put forth in applicant's claim 3 is anticipated by the teachings of Snyder et al.

25. *The following is in regard to Claim 4.* As just shown, Snyder et al. teach a method of fitting in accordance with claim 3. The optimum threshold, discussed above, minimizes the overall probability of error (i.e. the likelihood of misclassification of the data). See paragraph 2 on page 803 of Snyder et al. Therefore, the method put forth in applicant's claim 4 is anticipated by the teachings of Snyder et al.

26. *The following is in regard to Claim 5.* As shown above, Snyder et al. teach a method of fitting in accordance with claim 3. As described in paragraph 1 on page 803 of Snyder et al., the optimum threshold separates or segments the data according to the various modes (relative maxima) present in the data. Therefore, the method put forth in applicant's claim 5 is anticipated by the teachings of Snyder et al.

27. *The following is in regard to Claim 6.* As shown above, Snyder et al. teach a method of fitting in accordance with claim 1. Furthermore, Snyder et al. suggest (see equation (5)) that the modeling function is expressible as a vector[1] whose elements are the plurality of parameters (i.e. means, variances, and a priori probabilities) associated with the said plurality of gaussians. In this manner, the teachings of Snyder et al. anticipate the method of fitting proposed by the applicant in claim 6.

28. *The following is in regard to Claim 9.* As shown above, Snyder et al. teach a method of fitting in accordance with claim 1. As mentioned above, with regard to claim 1, Snyder et al. teach that the basis functions are

normal gaussian distributions, with means μ_i and standard deviations σ_i, $i=1...d$. See equation (1) of Snyder et al. Furthermore, the parameter set Θ associated with these basis functions consists of the means μ_i and standard deviations σ_i, $i=1...d$. See equation (5) of Snyder et al.

29. *The following is in regard to Claim 11.* As shown above, Snyder et al. teach a method of fitting in accordance with claim 1. The input data being fitted is in the form of a mutimodal histogram. See paragraph 1 on page 803 of Snyder et al. Therefore, the method of fitting proposed by the applicant in claim 11 is anticipated by the teachings of Snyder et al.

30. *The following is in regard to Claim 12.* As shown above, Snyder et al. teach a method in accordance with claim 1. As mentioned by Snyder et al., the objective function H is minimized with respect to the parameter set (Θ). See the last paragraph on page 803 of Snyder et al. to the first paragraph on page 804 of Snyder et al. As discussed above, with regard to claim 1, this minimization implies that a stopping criteria (e.g. $\frac{\partial H}{\partial \Theta} = 0$ – see paragraph 1 on page 804 of Snyder et al.) be compared to the objective function.

The objective function H can be considered a fitness function, in a similar vein as the applicant, since it is a function providing a measure of the goodness-of-fit of the model to the input data. In this way, the method put forth by the applicant in claim 12 is anticipated by the teachings of Snyder et al.

31. *The following is in regard to Claim 13.* As shown above, Snyder et al. teach a method in accordance with claim 12. Again, with regard to Snyder et al.'s fitting technique, the optimization involves the minimization of the objective function H with respect to the set of parameters Θ. As mentioned above, with regard to claim 12, the objective function can be considered a fitness function. Furthermore, it is clear from the form of H, shown in equation (4) of Snyder et al., that H is a measure of the magnitude of the fit error between the modeling function and the input data. In fact, to minimize H is to minimize this error, and vice versa. In this sense, the fitting technique taught by Snyder et al., optimizes the fitting function H by minimizing the fit error between the modeling function and the input data. Given this, it is clear that the method proposed by the applicant in claim 13 is anticipated by the teachings of Snyder et al.

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1 Technically, equation (5) of Snyder expresses the parameter set representing the modeling function as a set. Clearly, this set can be trivially expressed as a vector. While a set and vector are mathematically different, for the purposes of the algorithm disclosed by Snyder et al. and the method proposed by the applicant, they both represent collections of data and, therefore, can be treated as the same.

32. *The following is in regard to Claims 14, 16-19, 22, and 24-26.* These claims recite substantially the same limitations as claims 1, 3-6, 9, and 11-13, respectively. Therefore, with regard to claims 14, 16-19, 22, and 24-26, remarks analogous to those presented above with regard to claims 1, 3-6, 9, and 11-13 are, respectively, applicable.

Rejections Under U.S.C. § 103(a)

33. The following is a quotation of 35 U.S.C. 103(a) which forms the basis for all obviousness rejections set forth in this Office action:

> (a) A patent may not be obtained though the invention is not identically disclosed or described as set forth in section 102 of this title, if the differences between the subject matter sought to be patented and the prior art are such that the subject matter as a whole would have been obvious at the time the invention was made to a person having ordinary skill in the art to which said subject matter pertains. Patentability shall not be negatived by the manner in which the invention was made.

34. Claim 27-32, 34-35, 36-41, and 43-44 are rejected under 35 U.S.C. 103(a) as being unpatentable over Snyder et al., in view of Neves et al. ("A Study of a Non-Linear Optimization Problem Using a Distributed Genetic Algorithm", International Conference on Parallel Processing, 1996).

35. *The following is in regard to Claim 2.* As discussed above, Snyder et al. disclose a method of fitting that is in accordance with claim 1. The fitting technique of Snyder et al. further comprises:

a. The step of altering said plurality of function parameters. This is inherent to the minimization of objective function H with respect to the parameter set Θ discussed in the last paragraph of page 803 of Snyder et al. The goal of the procedure is to find the parameter set Θ that minimizes the objective function. This minimizing set generally involves altering the original set to satisfy the constraints of minimization.

However, Snyder et al. does not teach a fitting method, in accordance with claim 1, further comprising:

b. The step of altering said total number of functions.

c. Repeating:

i. Generating a modeling function based on said plurality of function parameters.

ii. Determining an objective function that measures the fitting error between said modeling function and the data.

iii. Comparing said fitting error to stopping criteria to determine if said stopping criteria is satisfied.

if, at the comparing step, the fitting error does not satisfy the stopping criteria.

36. Neves et al. present non-linear least square fitting (which is the essentially the task being performed by the applicant's claimed fitting method and by that of Snyder et al.) as an unconstrained optimization problem. In a manner similar to Snyder et al., Neves et al. construct the optimization problem in the following way. Find parameter set X such that:

$$\min_X \sum_{i=1}^{m} (y(t_i) - f(t_i, X))^2 \qquad (34.1)$$

See paragraph 1 in Section 4, METHODOLOGY, on page II-31 of Neves et al. Their solution to this problem is based on a genetic algorithm. See Abstract and Section 1, INTRODUCTION, of Neves et al.

37. With regard to claim 2, by virtue of the genetic algorithm used, Neves et al. teach a method of non-linear least squares fitting comprising:

b. The step of altering said total number of functions. Refer to section 2, BACKGROUND. The discussion therein relates to the theoretical basis of genetic algorithms. As discussed there (last paragraph of Neves et al.'s BACKGROUND), genetic algorithms begin with an initial population New individuals (states in the search space) are introduced and individuals of the current or prior generations are eliminated based on their fitness. It should be understood that, with regard to the methodology proposed in section 4 of Neves et al., the search space is the space of all potential parameter sets X. Each of these parameter sets corresponds to a function $f(t,X)$ in a bijective manner. Therefore, as the number of parameter set candidates changes through successive generations, so to does the total number of corresponding functions.

c. Repeating:

i. Generating a modeling function based on said plurality of function parameters.

ii. Determining an objective function that measures the fitting error between said modeling function and the data.

iii. Comparing said fitting error to stopping criteria to determine if said stopping criteria is satisfied.

if, at the comparing step, the fitting error does not satisfy the stopping criteria. Again, this is inherent to the genetic algorithm of Neves et al. During each generation of the algorithm, parameter sets *X* are generated and the functions *f(t,X)* are evaluated. The objective function (e.g. 34.1 above) is evaluated (where it is clear that 34.1 measures the fitting error). The algorithm continues until it converges to a global optimum (see section 2, BACKGROUND, of Neves et al.).

38. Note from the preceding discussion that both Neves et al. and Snyder attempt to solve the same problem, that is, minimizing the sum of the squared errors between the modeling function and the input data. It would be well within the capabilities of one of ordinary skill in the art to utilize a genetic algorithm of Neves et al. to find the global minimum of the objective function *H* in the fitting technique of Snyder et al., particularly since Neves et al. have demonstrated the use the algorithm in minimizing the sum of the squared errors between the modeling function and the input data. (Note the objective functions of Neves et al. and Snyder et al. are the same). The advantages of applying genetic algorithms to optimization problems, involving the minimization of the sum of the squared errors between the modeling function and the input data, are, among other things, that these algorithms converge, unsupervised, to a *global* minimum, easily accommodate a variety of constraints, are self-adaptive (in the sense that bad solutions are eliminated without intervention) and are relatively insensitive to initial parameters such as population size, when compared to other optimization methods. Given these advantages of genetic algorithms and their demonstrated applicability to optimization problems involving the minimization of the sum of the squared errors between the modeling function and the input data, it would have been obvious to one of ordinary skill in the art, at the time of the applicant's claimed invention, to use the genetic algorithm of Neves et al. to minimize the objective function (fitting error) of the fitting technique taught by Snyder et al. In doing so, one would obtain a method of fitting that conforms to all limitations of claim 2.

39. *The following is in regard to Claim 7.* As just shown, the teachings of Snyder et al. and Neves et al. can be combined in such a way as to satisfy all limitations of claim 2. Genetic algorithms proceed through successive

generations in an evolutionary manner. See section 2 of Neves et al. The altering of the number of parameter set candidates and, hence, the total number of basis functions takes place over successive generations. As mentioned above, with respect to claim 1, the parameter sets may change through successive generations, with respect to their parents (see section 2 of Neves et al.), as they tend toward minimization. In this way, the teachings of Snyder et al. and Neves et al., when combined in the manner discussed above, produce a fitting method in accordance with claim 7.

40. *The following is in regard to Claim 8.* As just shown, the teachings of Snyder et al. and Neves et al. can be combined in such a way as to satisfy all limitations of claim 7. In genetic algorithms, mutation and crossover are standard operations used to evolve the data toward optimization. See, for example, Fig. 1 of Neves et al. and column1, last paragraph on page II-31. In this way, the teachings of Snyder et al. and Neves et al., when combined in the manner discussed above, produce a fitting method in accordance with claim 8.

41. *The following is in regard to Claims 15 and 20-21.* These claims recite substantially the same limitations as claims 2 and 7-8, respectively. Therefore, with regard to claims 15 and 20-21, remarks analogous to those presented above with regard to claims 2 and 7-8 are, respectively, applicable.

42. *The following is in regard to Claim 27.* Snyder et al. describe a method for determining optimum thresholds, used to separate the various modes present in input image data (i.e. segmenting the image), by fitting of a plurality of sub-population functions (a mixture of gaussian probability density functions (pdfs)) to data. See *Section I. Introduction*, paragraphs 1-2 on page 803 of Snyder et al. This segmentation technique comprises steps of:

a. Producing a histogram of the image, having histogram data. The input data being fitted is in the form of a mutimodal histogram. See paragraph 1 on page 803 of Snyder et al.

b. Defining a plurality of functions (these functions will be referred to, interchangeably, with *basis functions* henceforth in this document) according to a plurality of function parameters and a total number of functions. See *Section I. Introduction*, paragraphs 2 on page 803 of Snyder et al. Note, in particular, equation (1). Equation (1) consists of a plurality of gaussians (i.e. $\left\{\frac{1}{\sqrt{2\pi\sigma_i}}\exp\left[-\frac{(x-\mu_i)^2}{\sigma_i^2}\right]\right\}_{i=1\ldots d}$) which are dependant on the sets parameters $\{\mu_i, \sigma_i\}_{i=1\ldots d}$. Also defined is a total number of functions d.

c. Generating a modeling function based on said plurality of function parameters. See *Section I. Introduction*, paragraphs 2 on page 803 of Snyder et al. Note, in particular, equation (1). The modeling function is $h(x)$.

d. Determining an objective function measuring the fitting error between said modeling function and the data. See the last paragraph on page 803 of Snyder et al. The value H defined in equation (4) of Snyder et al. can be considered an objective function measuring the fitting error between said modeling function ($h(x)$)and the data (h_j).

e. Comparing said fitting error to stopping criteria to determine if said stopping criteria is satisfied. This is implied by the minimization of the objection function (H) discussed in the last paragraph on page 803 of Snyder et al. to the first paragraph on page 804 of Snyder et al. It would be understood by one of ordinary skill in the art that such a minimization would involve a comparison of H, which is indicative of the fitting error, to a stopping criteria (i.e. a value considered minimal).

f. i. Altering said plurality of function parameters. This is inherent to the minimization of objective function H with respect to the parameter set Θ discussed in the last paragraph of page 803 of Snyder et al. The goal of the procedure is to find the parameter set Θ that minimizes the objective function. This minimizing set generally involves altering the original set to satisfy the constraints of minimization.

g. Specifying at least a first threshold value delineating said plurality of functions if said fitting error satisfies said stopping criteria. Snyder et al. disclose determining an optimum threshold that delineates said plurality of functions. See the second paragraph of Section I. *Introduction* on page 803 of Snyder et al. Note in particular equation (2). Also note that this threshold is obtained after the minimization of the objective function has been achieved, which implies satisfaction of the stopping criteria.

However, Snyder et al. does not teach:

ii. Altering said total number of functions.

iii. Repeating said generating, determining, and comparing steps if said fitting error does not satisfy said stopping criteria.

in item (f) above.

42. As discussed above, with regard to claim 2, Neves et al. disclose a fitting technique that minimizes an objective function (the sum of the square errors) with respect to a parameter set through the use of a genetic algorithm. By virtue of the genetic algorithm used, Neves et al. teach a method of non-linear least squares fitting comprising:

ii. The step of altering said total number of functions. Refer to section 2, BACKGROUND. The discussion therein relates to the theoretical basis of genetic algorithms. As discussed there (last paragraph of Neves et al.'s BACKGROUND), genetic algorithms begin with an initial population New individuals (states in the search space) are introduced and individuals of the current or prior generations are eliminated based on their fitness. It should be understood that, with regard to the methodology proposed in section 4 of Neves et al., the search space is the space of all potential parameter sets *X*. Each of these parameter sets corresponds to a function $f(t,X)$ in a bijective manner. Therefore, as the number of parameter set candidates changes through successive generations, so to does the total number of corresponding functions.

iii. Repeating said generating, determining, and comparing steps if said fitting error does not satisfy said stopping criteria. Again, this is inherent to the genetic algorithm of Neves et al. During each generation of the algorithm, a parameter sets *X* are generated and the functions $f(t,X)$ evaluated. The objective function (e.g. 34.1 above) is evaluated (where it is clear that 34.1 measures the fitting error). The algorithm continues until it converges to a global optimum (see section 2, BACKGROUND, of Neves et al.).

43. Note from the preceding discussion that, with regard to the fitting, both Neves et al. and Snyder attempt to solve the same problem, that is, minimizing the sum of the squared errors between the modeling function and the input data. It would be well within the capabilities of one of ordinary skill in the art to utilize a genetic algorithm of Neves et al. to find the global minimum of the objective function *H* in the segmentation technique of Snyder et al., particularly since Neves et al. has demonstrated the use the algorithm in minimizing the sum of the squared errors

between the modeling function and the input data. (Note the objective functions of Neves et al. and Snyder et al. are the same). The advantages of applying genetic algorithms to optimization problems, involving the minimization of the sum of the squared errors between the modeling function and the input data, are, among other things, that these algorithms converge, unsupervised, to a *global* minimum, easily accommodate a variety of constraints, are self-adaptive (in the sense that bad solutions are eliminated without intervention) and are relatively insensitive to initial parameters such as population size, when compared to other optimization methods. Given these advantages of genetic algorithms and their demonstrated applicability to optimization problems involving the minimization of the sum of the squared errors between the modeling function and the input data, it would have been obvious to one of ordinary skill in the art, at the time of the applicant's claimed invention, to use the genetic algorithm of Neves et al. to minimize the objective function (fitting error) in the fitting segmentation technique taught by Snyder et al. In doing so, one would obtain a method of specifying thresholds for the purposes of segmentation that conforms to all limitations of claim 27.

44. *The following is in regard to Claim 28.* As just shown, the teachings of Snyder et al. and Neves et al. can be combined in such a way as to satisfy all limitations of claim 27. The optimum threshold, discussed above, minimizes the overall probability of error (i.e. the likelihood of misclassification of the data). See paragraph 2 on page 803 of Snyder et al. In this way, the method of specifying thresholds for the purposes of segmentation obtained by combining the teachings of Snyder et al. and Neves et al., in the manner discussed above, conforms to all limitations of claim 28.

45. *The following is in regard to Claim 29.* As shown above, the teachings of Snyder et al. and Neves et al. can be combined in such a way as to satisfy all limitations of claim 27. Furthermore, Snyder et al. suggest (see equation (5)) that the modeling function is expressible as a vector[1] whose elements are the plurality of parameters (i.e. means, variances, and a priori probabilities) associated with the said plurality of gaussians. In this way, the method of specifying thresholds for the purposes of segmentation obtained by combining the teachings of Snyder et al. and Neves et al., in the manner discussed above, conforms to all limitations of claim 29.

46. *The following is in regard to Claim 30.* As shown above, the teachings of Snyder et al. and Neves et al. can be combined in such a way as to satisfy all limitations of claim 27. Genetic algorithms proceed through successive generations in an evolutionary manner. See section 2 of Neves et al. The altering of the number of parameter set

candidates and, hence, the total number of basis functions takes place over successive generations. As mentioned above, with respect to claim 27, the parameter sets may change through successive generations, with respect to their parents (see section 2 of Neves et al.), as they tend toward minimization. In this way, the method of specifying thresholds for the purposes of segmentation obtained by combining the teachings of Snyder et al. and Neves et al., in the manner discussed above, conforms to all limitations of claim 30.

47. *The following is in regard to Claim 31.* As just shown, the teachings of Snyder et al. and Neves et al. can be combined in such a way as to satisfy all limitations of claim 30. In genetic algorithms, mutation and crossover are standard operations used to evolve the data toward optimization. See, for example, Fig. 1 of Neves et al. and column1, last paragraph on page II-31. In this way, the method of specifying thresholds for the purposes of segmentation obtained by combining the teachings of Snyder et al. and Neves et al., in the manner discussed above, conforms to all limitations of claim 31.

48. *The following is in regard to Claim 32.* As shown above, the teachings of Snyder et al. and Neves et al. can be combined in such a way as to satisfy all limitations of claim 27. As mentioned above, with regard to claim 27, Snyder et al. teach that the basis functions are normal gaussian distributions, with means μ_i and standard deviations σ_i, $i=1...d$. See equation (1) of Snyder et al. Furthermore, the parameter set Θ associated with these basis functions consists of the means μ_i and standard deviations σ_i, $i=1...d$. See equation (5) of Snyder et al. In this way, the method of specifying thresholds for the purposes of segmentation obtained by combining the teachings of Snyder et al. and Neves et al., in the manner discussed above, conforms to all limitations of claim 32.

49. *The following is in regard to Claim 34.* As shown above, the teachings of Snyder et al. and Neves et al. can be combined in such a way as to satisfy all limitations of claim 27. As mentioned by Snyder et al., the objective function H is minimized with respect to the parameter set (Θ). See the last paragraph on page 803 of Snyder et al. to the first paragraph on page 804 of Snyder et al. As discussed above, with regard to claim 1, this minimization implies that a stopping criteria (e.g. $\frac{\partial H}{\partial \Theta} = 0$ – see paragraph 1 on page 804 of Snyder et al.) be compared to the objective function. The objective function H can be considered a fitness function, in a similar vein as the applicant, since it is a function providing a measure of the goodness-of-fit of the model to the input data. In this way, the

method of specifying thresholds for the purposes of segmentation obtained by combining the teachings of Snyder et al. and Neves et al., in the manner discussed above, conforms to all limitations of claim 34.

50. *The following is in regard to Claim 35.* As just shown, the teachings of Snyder et al. and Neves et al. can be combined in such a way as to satisfy all limitations of claim 34. Again, with regard to the fitting taught by Snyder et al., the optimization involves the minimization of the objective function H with respect to the set of parameters Θ. As mentioned above, with regard to claim 34, the objective function can be considered a fitness function. Furthermore, it is clear from the form of H, shown in equation (4) of Snyder et al., that H is a measure of the magnitude of the fit error between the modeling function and the input data. In fact, to minimize H is to minimize this error, and vice versa. In this sense, the fitting technique taught by Snyder et al., optimizes the fitting function H by minimizing the fit error between the modeling function and the input data. In this way, the method of specifying thresholds for the purposes of segmentation obtained by combining the teachings of Snyder et al. and Neves et al., in the manner discussed above, conforms to all limitations of claim 35.

51. *The following is in regard to Claims 36-41 and 43-44.* These claims recite substantially the same limitations as claims 27-32 and 34-35 respectively. Therefore, with regard to claims 36-41and 43-44, remarks analogous to those presented above with regard to claims 29-32 and 34-35 are, respectively, applicable.

52. Claims 10 and 23 are rejected under 35 U.S.C. 103(a) as being unpatentable over Snyder et al., in view of Levine ("Statistics for Managers Using Microsoft Excel: Chapter 14 – Multiple Regression Models", 1999).

53. *The following is in regard to Claim 10.* As shown above, Snyder et al. describe a fitting technique that is in accordance with claim1. Snyder et al., however, do not suggest the usage of an F-test to evaluate the relative contribution of each of the basis functions when comparing the objective function to the stopping criteria.

54. The F-test is a well-known statistical test used to determine whether two populations have equal variances. It is frequently used to analyze the goodness-of-fit of linear regression models. (Least-squares fitting, such as performed in the applicant's claimed fitting method and discussed by both Snyder et al. and Neves et al., is a form of linear regression). A common application of the F-test is to analyze the contribution of an independent variable to the goodness-of-fit of a model that depends on multiple independent variables. See Levine slides 14-18 to 14-23.

55. Note that the mixture models discussed by Snyder et al. (and those used in the applicant's fitting method) represent models (i.e. the modeling functions) that depend on multiple independent variables (i.e. the basis functions). Consequently, the F-test can be used to analyze the modeling functions of Snyder et al. in the manner described above. It would be straightforward for one of ordinary skill in the art to incorporate the F-test into the objective function of Snyder, thereby providing an additional measure of the goodness-of-fit of the modeling function to the input data. Clearly, one is motivated to do so to provide a more precise measure of the goodness-of-fit of the modeling function to the input data, in addition to providing a measure of the optimal number of basis functions to use in the modeling function[2]. Given the straightforwardness of making such a modification and its clear advantages, it would have been obvious to one of ordinary skill in the art, at the time of the applicant's claimed invention, to incorporate the F-test into the objective function of the fitting technique taught by Snyder et al. In doing so, one would obtain a fitting method, in accordance with claim 1, further comprising using an F-test to evaluate the relative contribution of each of the basis functions when comparing the objective function to the stopping criteria. Such a fitting method conforms to all limitations of claim 10.

56. *The following is in regard to Claim 23.* This claim recites substantially the same limitations as claim 10. Therefore, with regard to claim 23, remarks analogous to those presented above with regard to claim 10 are applicable.

57. Claim 33 and 42 are rejected under 35 U.S.C. 103(a) as being unpatentable over Snyder et al., in view of Neves et al, as applied to claims 27 and 36, respectively, in further view of Levine.

58. *The following is in regard to Claim 33.* As shown above, the teachings of Snyder et al. and Neves et al. can be combined in such a way as to satisfy all limitations of claim 27. However, neither Snyder et al. nor Neves et al. suggest the usage of an F-test to evaluate the relative contribution of each of the basis functions when comparing the objective function to the stopping criteria.

2 Since the F-test provides a measure of the contribution of a basis function to the goodness-of-fit of the modeling function, modeling functions with extraneous basis functions (i.e. basis functions that make little contribution to the goodness-of-fit) can be considered less optimal.

59. The F-test is a well-known statistical test used to determine whether two populations have equal variances. It is frequently used to analyze the goodness-of-fit of linear regression models. (Least-squares fitting, such as performed in the applicant's claimed fitting method and discussed by both Snyder et al. and Neves et al., is a form of linear regression). A common application of the F-test is to analyze the contribution of an independent variable to the goodness-of-fit of a model that depends on multiple independent variables. See Levine slides 14-18 to 14-23.

60. Note that the mixture models discussed by Snyder et al. (and those used in the applicant's claimed segmentation method) and the modeling function discussed by Neves et al. represent models (i.e. the modeling functions) that depend on multiple independent variables (i.e. the basis functions). Consequently, the F-test can be used to analyze the modeling functions of Snyder et al. (or Neves et al.) in the manner described above. It would be straightforward for one of ordinary skill in the art to incorporate the F-test into the objective function of Snyder, thereby providing an additional measure of the goodness-of-fit of the modeling function to the input data. Clearly, one is motivated to do so to provide a more precise measure of the goodness-of-fit of the modeling function to the input data, in addition to providing a measure of the optimal number of basis functions to use in the modeling function[2]. Given the straightforwardness of making such a modification and its clear advantages, it would have been obvious to one of ordinary skill in the art, at the time of the applicant's claimed invention, to incorporate the F-test into the objective function of the segmentation method, obtained by the combined teachings of Snyder et al. and Neves et al. In doing so, one would obtain a segmentation method, in accordance with claim 27, further comprising using an F-test to evaluate the relative contribution of each of the basis functions when comparing the objective function to the stopping criteria. Such a fitting method conforms to all limitations of claim 33.

61. *The following is in regard to Claim 42.* This claim recites substantially the same limitations as claim 33. Therefore, with regard to claim 42, remarks analogous to those presented above with regard to claim 33 are applicable.

Citation of Relevant Prior Art

62. The prior art made of record and not relied upon is considered pertinent to applicant's disclosure:

[1] *Learning Mixture Models Using a Genetic Version of the EM Algorithm.* Pattern Recognition Letters 21. July 2000. Martinez and Vitrià. Martinez et al. derive an optimal parameter set for a mixture of gaussian distributions used to model an observed data set. They employ a genetic algorithm to search the parameter space for a parameter set that maximizes (globally) the maximum likelihood (ML) of a parameter set (viz. Expectation Maximization). The derived model is combined with shape information to classify various patterns in an input image. The similarities between Martinez et al.'s methodology and the applicant's claimed fitting and segmentation methods should be apparent.

Any inquiry concerning this communication or earlier communications from the examiner should be directed to Kevin Siangchin whose telephone number is (703)305-7569. The examiner can normally be reached on 9:00am - 5:30pm, Monday - Friday.

If attempts to reach the examiner by telephone are unsuccessful, the examiner's supervisor, Amelia Au can be reached on (703)308-6604. The fax phone number for the organization where this application or proceeding is assigned is 703-872-9306.

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Examiner
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